RELIABILITY PREDICTION FOR ELECTRICAL - ELECTRONIC DEVICES: A COMPREHENSIVE REVIEW OF METHODS, CHALLENGES, AND FUTURE DIRECTIONS

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Abstract – Reliability prediction is fundamental to electronic system design, lifetime estimation, risk assessment, and maintenance planning. Over the past decades, diverse prediction approaches have emerged, spanning empirical handbook-based methods, physics-of-failure, life testing, state-space modeling, data-driven techniques, and hybrid frameworks. However, increasing system complexity and operating variability have revealed key limitations of empirical standards such as MIL-HDBK-217F and Telcordia SR-332, especially in physical interpretability, lifecycle coverage, and adaptability to modern applications. To address these challenges, this paper reviews and compares six representative reliability prediction models, highlighting their theoretical basis as well as their strengths and weaknesses. Particular attention is given to recent data-driven and hybrid approaches that combine physical insight with statistical learning to enhance prediction accuracy and operational relevance. From a lifecycle perspective, the paper also identifies research gaps and outlines directions toward more scalable, interpretable, and practically applicable reliability prediction frameworks for contemporary electronic systems.

Key words - Reliability prediction; electronic devices; empirical methods; physics of failure; data-driven models

1. Introduction

In electronics, reliability is regarded as one of the most important quality characteristics, having received sustained attention over several decades of electronic system development. This importance has become more evident as electronic devices have grown increasingly pervasive in daily life, with direct implications for safety, system stability, and maintenance costs. At the same time, electronic hardware is moving toward higher levels of integration and miniaturization, while assuming more critical functional roles within systems, thereby prolonging rather than eliminating long-standing reliability challenges. Under these conditions, ensuring uninterrupted operation without failure has become a primary concern in electronic product development [1], [2].

To accomplish this, the use of reliability prediction has been extensively used. Reliability prediction aims to estimate failure time and probability, drawing on operating conditions together with theoretical models or historical data; it is therefore commonly employed at the design stage and later used for maintenance planning and safety evaluation [3].

In the power sector, reliability prediction has been applied to the electrical subsystems of wind turbines, which are often regarded as among the most failure-prone parts of the system due to their exposure to combined environmental and operational stresses. In particular, power electronic devices within these subsystems experience aging and degradation mechanisms that have a direct impact on turbine availability and long-term performance [4]. Similar reliability issues are observed in the transportation sector, especially in fast electric vehicle charging equipment, where semiconductor switches, passive components, and charger assemblies are continuously subjected to high electrical and thermal loading, thereby influencing system lifetime and operational continuity [5].

Reliability prediction is particularly important in aerospace applications, where mission success depends on the combined performance of multiple electronic and electromechanical subsystems, typically in situations where extensive physical testing is impractical or prohibitively expensive [6]. At the same time, reliability issues have attracted growing interest in biomedical applications, especially in bioelectronic medicine, where wearable or implantable electronic devices must sustain stable operation over long durations while interacting with complex and dynamic biological environments [7]. Across these domains, reliability prediction is commonly used as an analytical tool to study degradation behavior and to anticipate failures in electronic devices and systems operating under demanding conditions. This, in turn, highlights the need for reliability prediction methods that are both accurate and practically relevant.

Reliability prediction methodologies have evolved progressively over time. Early approaches were primarily based on empirical formulations and reference handbooks, such as Telcordia and MIL-HDBK-217, which rely on accumulated field failure data together with standardized assumptions to provide reliability estimates. Classic review studies from this period, including Bowles [8], Denson [1], Jones et al. [9], and later Goel et al. [10], mainly focused on comparing empirical handbooks (e.g., MIL-HDBK-217, Bellcore, PRISM), reflecting a transitional phase in which process-related factors and operating conditions began to be considered, while the underlying paradigm remained largely handbook-driven.

These empirical practices were later complemented by physics-of-failure (PoF) models, aiming to explicitly describe dominant degradation mechanisms at the material and component levels and, in doing so, to offer enhanced physical interpretability [11], [12]. In contrast to handbook-based correction factors, failure mechanisms themselves

became the central modeling focus, as emphasized in Pecht et al. [13] and later in Irias et al. [14]. Furthermore, review studies in the domain of power electronics, such as [15], [16], and [17], offer comprehensive details on the degradation mechanisms at the physical level (e.g., interconnect reliability) and mission-based stress profiles that can be directly used for the prediction of the remaining useful life (RUL). However, the respective literature reviews are typically specific to the component/module level and do not allow the reader to achieve an overall perspective of the complex electronic systems, which encompass various technical branches.

When applied to contemporary electronic systems characterized by heterogeneous architectures, multi-physics interactions, and variable operating conditions, however, these conventional methodologies may show limited predictive flexibility and accuracy. This is particularly the case when system behavior deviates from predefined assumptions or when detailed failure information is unavailable. In response to these limitations, recent research has increasingly focused on data-driven and hybrid approaches that combine statistical learning with physics-based knowledge, with the objective of improving adaptability and extending the applicability of reliability prediction in complex electronic systems [2].

Nevertheless, despite the rather large amount of literature on reliability prediction methods that have been accumulated over the last three decades, there remain certain shortcomings in the available literature reviews, as reflected in the existing studies of [18] and [19], aiming to cover the broad range of reliability prediction methods including empirical, PoF, state space, and data-driven methods, while they are rather presented in an unconnected way and on an introductory level, without fully covering the latest advancements in the respective domain, such as the combined or hybrid methods.

Table 1. *Overview and methodological coverage of representative review studies on reliability prediction*

Ref.	Method Coverage						Lifecycle Coverage	Primary Focus
	Empirical	PoF	Life Testing	State-Space	Data-Driven	Hybrid		
[8]	✓	✗	✗	✗	✗	✗	Infant failures	Empirical standards comparison
[13]	✓	✓	✗	✗	✗	✗	Design, Manufacturing, Operation	Design-for-Reliability, PoF-oriented failure prevention
[1]	✓	✓	✓	✗	✗	✗	Early design	MIL-HDBK-based prediction
[9]	✓	✗	✗	✗	✗	✗	Design, In-service	Empirical standards comparison
[25]	✓	✓	✗	✗	✗	✗	Design, Manufacturing, Operation	Lifecycle-oriented method selection
[10]	✓	✓	✗	✗	✗	✗	Design, Useful life, Wearout	MIL-HDBK vs PRISM
[15]	✗	✓	✓	✗	✗	✗	Design, Validation	Power electronics PoF
[14]	✗	✓	✗	✗	✗	✗	Design, Operation	PoF field application challenges
[18]	✓	✓	✓	✗	✗	✗	Full lifecycle (design to wearout)	Comparative overview of reliability prediction methods
[16]	✓	✓	✓	✗	✗	✗	Design to in-service (PHM)	Power electronics lifetime
[19]	✓	✓	✓	✓	✓	✗	Early design to useful life	Multi-method introductory review
[17]	✗	✓	✓	✗	✗	✗	Design, Validation, Operation	Power electronics reliability
[2]	✓	✓	✓	✓	✓	✓	Full lifecycle across critical industries	Cross-industry reliability trends & frameworks
[20]	✗	✗	✗	✗	✓	✗	Operation	ML -focused
[22]	✗	✗	✗	✓	✗	✗	Operation	State-space reliability modeling
[23]	✓	✓	✓	✗	✗	✗	Design, Manufacturing, Operation	ALT and DoE-based testing
[24]	✓	✓	✓	✓	✗	✗	Design, Manufacturing, Operation	Reliability model comparison for power converters
[21]	✗	✓	✗	✗	✓	✓	Operation	Physics-informed ML
This review	✓	✓	✓	✓	✓	✓	**Full lifecycle with method-to-stage mapping**	**Lifecycle-oriented method comparison framework**

Conversely, review studies that focus specifically on machine learning (ML) techniques, such as Xu et al. [20] or physics-informed learning, such as Li et al. [21] tend to concentrate on algorithmic details, while more traditional reviews centered on state-space models, such as Gaurav et al. [22] or on accelerated life testing (ALT) combined with design of experiments (DoE), such as Indmeskine et al. [23], commonly treat these approaches in isolation. Meanwhile, several more recent standard-comparison review studies, such as Navamani et al. [24], provide extensive comparative assessments across multiple conventional reliability prediction paradigms, including empirical handbook-based methods, physics-of-failure models, life testing approaches, and state-space formulations; however, these studies generally stop short of establishing systematic connections to emerging data-driven, machine learning–based, or hybrid reliability prediction frameworks. More importantly, although Nor et al. [2] represent one of the few review efforts that explicitly encompass all six major reliability prediction methodologies across multiple critical industries, their

analysis primarily emphasizes cross-industry trends and high-level methodological characteristics, rather than offering a unified, lifecycle-oriented framework that systematically maps methods to specific lifecycle stages and practical engineering use cases. Consequently, with the exception of the early classification-oriented review by Foucher et al. [25], there has been extremely limited effort to fully integrate Empirical, PoF, Life testing, State-space, Data-driven, and Hybrid approaches into a single overarching reference framework. Table 1 summarizes several representative review studies in this context.

Compared with existing reviews, the present work makes four specific contributions. First, a lifecycle-oriented mapping framework is constructed that systematically associates each of the six reliability prediction method families with the specific product lifecycle stages at which they are most applicable, based on the information available and the modelling objective. Second, a unified comparative taxonomy is introduced that evaluates all six methods against a consistent set of structured criteria (required inputs, assumptions, outputs, calibration needs, uncertainty handling, interpretability, and failure mode coverage), enabling direct cross-method comparison without switching between heterogeneous evaluation frameworks. Third, hybrid approaches are analysed not merely as a collection of techniques but as a unifying paradigm that bridges mechanism-level and system-level modelling, with explicit attention to integration architectures and their lifecycle context. Fourth, the analysis is consistently oriented toward actionable engineering applications, connecting methodological properties to practical deployment constraints and decision-support requirements.

2. Reliability metrics and evaluation foundations

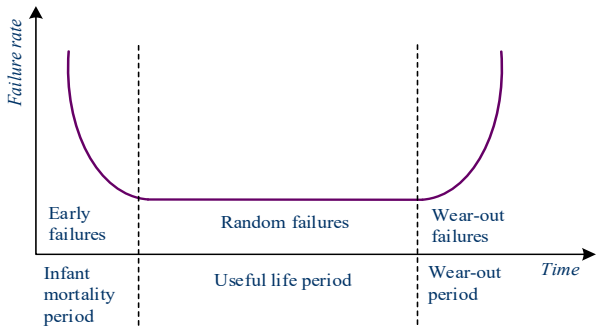

Figure 1. *Bathtub curve*

The failure rate refers to the frequency at which a system or component fails. This is calculated by dividing the number of failures by the time interval. The failure rate varies throughout the life of the product and is not constant at every moment. Figure 1 shows the failure rates over a given period of time, popularly referred to as the bathtub curve. The curve exhibits three distinct phases [26]:

1. Infant mortality phase: Marked by high failure rates; however, these are decreasing because of the correction of design, production, or initial installation problems.

2. Useful life phase: Represents a period of relatively constant and low failure rate, where random, non-systematic failures occur under normal operating conditions.

3. Wear-out phase: This phase registers more failures because the components age and wear out owing to fatigue, corrosion, or material breakdown.

To effectively measure and improve the reliability of electronic systems, several key parameters must be considered. These parameters, which are determined by the technology used, design measures, customer needs, and specific application demands, are Mean Time to Failure (MTTF), Mean Time to Repair (MTTR), failure rate, and system availability [26].

2.1. Reliability function

The reliability function $R(t)$ represents the probability that a system operates normally up to time t without failure. Given the failure time probability density function $f(t)$, it is defined as:

$$R(t) = P(T > t) = \int_t^{\infty} f(u)du = 1 - F(t) \tag{1}$$

where, T is the time-to-failure (TTF), $f(t)$ is the probability density function (PDF), and $F(t)$ is the cumulative distribution function (CDF) of failure.

2.2. Failure rate

The instantaneous failure rate at time t, denoted $\lambda(t)$, is defined as:

$$\lambda(t) = \frac{f(t)}{R(t)} \tag{2}$$

In many models, a constant failure rate $\lambda(t) = \lambda$ is assumed to simplify the analysis, and the reliability function becomes:

$$R(t) = e^{-\lambda t} \tag{3}$$

2.3. Mean time to failure

For non-repairable systems, the mean time to failure is the expected value of the lifetime of the system:

$$MTTF = \int_0^{\infty} R(t)\,dt \tag{4}$$

Under the assumption of a constant failure rate:

$$MTTF = \frac{1}{\lambda} \tag{5}$$

2.4. Mean time between failure, repair rate, and availability

For repairable systems, the operating cycle includes both the time to failure and the time required to restore the system. In such cases, the mean time between failures (MTBF) is given by:

$$MTBF = MTTF + MTTR \tag{6}$$

where MTTR is mean time to repair. The repair rate is defined as the reciprocal of the repair time:

$$\mu = \frac{1}{MTTR} \tag{7}$$

The availability of a system, denoted A_S, is the proportion of time the system is in an operational state under steady-state conditions:

$$A_S = \frac{MTBF}{MTBF + MTTR} = \frac{\mu}{\lambda + \mu} \quad (8)$$

This expression highlights that availability increases as the repair rate μ increases relative to the failure rate λ. In other words, when the repair time is significantly shorter than the operating time (i.e., $\mu \gg \lambda$), the availability approaches 1, meaning that the system is almost always operational.

3. Classification of reliability prediction methods

The scope of the reliability prediction problem covers a broad range of approaches that vary mostly in terms of model assumptions, input data requirements, and the extent to which physical knowledge or statistical inference is incorporated. Within the range of methodologies, the reliability measures mentioned in Section 2, such as the reliability function, the failure rate, the MTTF, the MTBF, and the MTTR, form the general terms of system reliability. Depending on the chosen methodology, the measures mentioned can either be model parameters or prediction outputs.

For the purpose of organized discussion, the discussed methodologies are grouped into two main categories based on the conceptual basis of the methodologies as well as the degree of modeling complexity. The first category of methodologies includes conventional approaches like empirical handbook-based methodologies, physics-of-failure modeling approaches, and testing methodologies, among others. These are standardized methodologies that are widely in use. The second category of methodologies includes state-space modeling, data-driven approaches, hybrid approaches, among others. These approaches are designed to represent system dynamics, operational variability, and uncertainty more explicitly. Within each category, representative studies are discussed to clarify the characteristic features of the methods, as well as their typical advantages and limitations across different stages of the system lifecycle.

3.1. Conventional approaches

These sections capture popular reliability prediction methods of earlier decades.

3.1.1. Empirical-based methods

Empirical prediction models, based on empirical data, utilize curve-fitting methods that evolve from failure history data collected from the field, in-house testing, or manufacturer data [27], [28]. These models are highly efficient in predicting the reliability of similar components or systems that have been tested, while also permitting limited parameter tuning to reflect engineering judgment and application-specific conditions. Commonly used standards that form the basis of these methods include MIL-HDBK-217F, Telcordia SR-332, FIDES Guide, IEC 61709, IEC 62380, and RIAC 217Plus [29-34].

Empirical reliability standards are essentially formulated to estimate the failure rate of electronic components or systems by starting from a reference value and applying a set of correction factors that reflect actual operating conditions. The reference failure rate is usually obtained from historical field data or standardized reliability databases. Correction factors are then introduced to capture the influence of the operating environment, thermal and electrical stress, duty cycles, quality levels, manufacturing processes, as well as usage or mission profiles. This general structure can be expressed as:

$$\lambda = \lambda_{ref} \prod_{i=1}^{N} \pi_i \quad (9)$$

where λ represents the predicted failure rate, λ_{ref} is the reference failure rate under nominal conditions, and π_i denotes the correction factors associated with the relevant stress and usage parameters. The estimated failure rate is subsequently used to evaluate the reliability function and the MTTF.

Table 2. *Limitations of commonly used empirical reliability prediction standards*

Standard	Description of limitations
MIL-HDBK-217F	Decommissioning [35].
Telcordia SR-332	Limited to telecom applications, less detailed for other industries, assumptions may not be held universally [24].
FIDES	Neglects physical wear-out mechanisms, constant failure-rate assumption, and subjective parameters affecting lifetime estimates [36].
IEC 61709	Packaging-related omissions, neglect of key physical interactions [37].
IEC 62380	Outdated, lack of updates, high cost, and limited access [37].
RIAC 217Plus	Large prediction errors for certain component families, limited consideration of humidity effects, and high complexity in system-level assessment [38].

These standards were initially adopted for their practicality, standardized analytical frameworks, and access to comprehensive historical failure data, which supported their extensive use in engineering practice for many years. Nevertheless, subsequent studies have identified several inherent limitations that limit their effectiveness in real-world applications, as summarized in Table 2.

3.1.2. Physics-of-failure methods

PoF methodologies address the physical, chemical, thermal, and mechanical mechanisms responsible for degradation and failure in components and systems. Rather than relying on purely empirical correlations, PoF is founded on materials science principles and known physical laws. As a result, lifetime prediction can be performed by explicitly relating operational loads to the induced stresses, the associated damage accumulation, and the final failure under realistic operating conditions. Within a typical PoF framework, lifetime prediction follows a structured sequence: (i) characterization of the mission profile and loading conditions; (ii) transformation of operational loads into relevant stresses, such as thermal, electrical, or mechanical stresses; (iii) modeling of damage evolution associated with the dominant failure mechanisms; and (iv) estimation of TTF [39]. Based on this framework, several representative analytical and semi-empirical PoF lifetime models have been widely adopted in reliability studies.

a. Arrhenius model

This classical model predicts how high temperatures assist chemical reactions and is used extensively in

reliability studies on the temperature sensitivity of devices. The model can be expressed as follows [19]:

$$L(T) = A \exp\left(\frac{E_a}{kT}\right) \quad (10)$$

where, $L(T)$ is the life characteristic related to the temperature, A is the scaling factor, E_a is the activation energy, k is the Boltzmann constant, and T is the absolute temperature.

The Arrhenius model assumes a single dominant failure mechanism, which limits its applicability under multi-stress operating environments.

b. Eyring model:

As an extension of the Arrhenius model, the Eyring model includes additional stress parameters such as voltage, humidity, and mechanical stress. It is formulated as [19]:

$$L(T,S) = AT^{\alpha} \exp\left[\frac{E_a}{kT} + \left(B + \frac{C}{T}\right)S\right] \quad (11)$$

Where, A, α, B, C are constants; S is the stress factor; and T is the absolute temperature.

c. Coffin-Manson model for fatigue:

This model takes into account fatigue due to thermal cycling, which occurs in solder joints or parts that undergo repeated thermal shocks. The model is written as [19]:

$$N_f = Af^{-\alpha}\Delta T^{-\beta} G(T_{\max}) \quad (12)$$

Where, N_f is the number of cycles to failure; A is the material-dependent coefficient; f is the cycling frequency; α and β are the empirical exponents; T is the temperature swing per cycle; and $G(T_{\max})$ is the Arrhenius term evaluated at the peak temperature.

Table 3. *Selected studies on the application and enhancement of PoF models in reliability prediction*

Ref.	Application object(s)	Key contribution(s)	Limitations
[40]	Hydraulic servo actuator	Developed a PoF model that accounts for component dependency and failure collaboration.	Neglecting dependencies among failure mechanisms
[41]	LED arrays	Integrated PoF and statistical models to capture interactions between luminous flux degradation and sudden failures.	No explicit modeling of fracture mechanisms.
[42]	Ball bearing	Proposed a PoF–Bayesian framework for multi-level failure modeling with probabilistic updating.	Single-component validation only; no solution for prior definition in data-scarce systems.
[43]	Two-component parallel system	Introduced the CCPoF method to model common-cause failures with time-dependent degradation effects.	Considers only thermal degradation; no expert validation.
[44]	Printed circuit boards (PCB)	Combined PoF and Monte Carlo simulation to predict failure time under coupled thermal, vibration, and manufacturing variability effects.	Simplifies the simulation model; neglects resonant interactions.
[45]	Condition-based monitoring sensor	Integrated PoF, finite element analysis (FEA) and failure mode and effect analysis (FMEA) to identify vibration-induced failure mechanisms at the design stage.	Ignore thermal loads and material anisotropy.
[46]	Electromagnetic relays	Proposed a PoF-based reliability model incorporating manufacturing variability, with parameters identified using long short-term memory (LSTM).	Incomplete failure mechanisms; considers only thermal stress; limited validation scope.

Recent studies summarized in Table 3 show that current PoF research is no longer limited to isolated, mechanism-level modeling. Hybrid frameworks are now more commonly adopted, mainly to address interaction effects, uncertainty, and system-level complexity. At the system level, tools such as Failure Modes and Effects Analysis (FMEA) or Failure Modes, Effects, and Criticality Analysis (FMECA) are often used to identify and prioritize relevant failure modes, which are then examined through physics-based modeling. Deterministic failure laws remain an important basis, but in many studies, they are combined with probabilistic inference, numerical simulation, or data-driven parameter identification in order to deal with incomplete material data and limited failure observations.

Despite these advances, the practical implementation of PoF is still constrained. Accurately characterizing stress, strain, and thermal fields under realistic operating conditions remains difficult, particularly when material and process information is incomplete, and failure mechanism modeling requires a high level of expertise [14]. The impact of these limitations is more evident in early design stages, where experimental measurements are often scarce or unavailable. Under such conditions, numerical field-solving techniques, especially the Finite Element Method (FEM), are used together with PoF to obtain physically consistent estimates of loading and degradation drives, supporting a more reliable evaluation of failure mechanisms [47], [48]

3.1.3. Life testing methodologies

Life testing represents a fundamental group of methods used in reliability prediction, in which failure data collected from experimental tests are employed to statistically infer the lifetime characteristics of a product. In practice, life testing approaches are generally divided into two principal categories, namely conventional life testing and Accelerated Life Testing (ALT). Within this framework, ALT plays a particularly important role for products that are designed for long service lifetimes or that must satisfy stringent reliability requirements [49].

In conventional life testing, a sufficiently large number of test samples are operated under normal use conditions

and are continuously monitored until failure takes place. The corresponding failure times are then examined using suitable statistical distributions, most commonly the Weibull distribution [50–52], to estimate reliability metrics such as the MTTF or the time-dependent reliability function. This method was originally well suited to earlier generations of products with relatively low reliability and short service lives, where failures could be observed within reasonable testing durations. Over time, improvements in product quality have significantly increased reliability and extended operational lifetimes, so that failures under normal use conditions now occur far less frequently. As a result, conventional life testing has become both time-consuming and costly, since increasingly long test periods and large sample sizes are required, which greatly limits its applicability in modern industrial practice [49].

As conventional life testing becomes increasingly impractical for highly reliable products, accelerated approaches have gradually gained attention. In this context, ALT subjects' products to stress levels that exceed those experienced under normal operating conditions, to shorten the time required for degradation and failure to occur and, consequently, enabling the collection of failure data within a feasible testing period. Depending on the dominant failure mechanisms involved, the applied stresses may include elevated temperature, voltage, mechanical loading, or other relevant environmental factors. The resulting failure data are subsequently interpreted to estimate product reliability under nominal use conditions by means of extrapolation. This procedure relies on assumed life–stress relationships that describe how time to failure varies with the applied stress level and is critically dependent on the assumption that the accelerated stresses do not activate failure mechanisms that are absent during normal operation [51]. When this assumption holds, ALT allows key reliability metrics to be estimated with substantially reduced testing time and sample size, making it particularly suitable for products characterized by high reliability and long expected service lifetimes.

In practical applications, it is also common for multiple stress factors to act simultaneously, while their combined effects are not always adequately captured by single-stress acceleration schemes. For this reason, multi-stress ALT configurations have increasingly been explored as a way to better reflect realistic operating environments; however, such approaches inevitably introduce additional complexity in experimental design, parameter identification, and data interpretation. In addition, the strong dependence on statistical models and distributional assumptions can further increase uncertainty in predicted results when testing conditions vary. These limitations have motivated the development of integrated approaches that aim to strengthen the linkage between experimental data and the underlying physical failure mechanisms [23], [53].

3.2. Advanced approaches

As discussed in the preceding sections, conventional reliability prediction methods have long served as the foundation for the assessment of electronic systems. However, their applicability is increasingly constrained by recent technological developments and growing system complexity. In particular, these methods are generally limited in their ability to capture intricate interactions among system elements and rarely exploit empirical usage or condition-monitoring data obtained during operation. As a result, their predictive capability may be insufficient when systems operate under varying or unforeseen conditions.

Addressing these limitations requires advanced approaches that can represent the dynamic behavior of electronic systems over time. These approaches allow the degradation process to be described explicitly, together with the associated uncertainty and variability originating from the operating environment and the system itself. Compared with conventional static or semi-empirical models, advanced methods are able to incorporate time-dependent information and to revise predictions when additional data become available. In addition, advanced approaches make use of data collected from testing, field operations, or monitoring activities. This capability enables more effective decisions to be made at different stages of the electronic system lifecycle, including design optimization, maintenance planning, and operation.

3.2.1. State-space models

State-space models (SSMs) have been extensively used as a mathematical framework for reliability prediction in complex dynamic systems, especially in situations where system behavior evolves over time and is influenced by uncertainty and changing operating conditions. Rather than relying on static or purely empirical descriptions, SSMs characterize system behavior through internal state variables, whose evolution follows probabilistic transition laws and is inferred from observable measurements [22], [54].

In many practical reliability applications, degradation processes cannot be measured directly. Instead, observable degradation signals are commonly treated as indirect indicators of the underlying physical degradation state. Within the state-space formulation, this assumption is naturally accommodated by defining a state transition model that describes the evolution of the hidden system state over time, and a measurement model that links the hidden state to observable degradation signals [55]. Formally, the state evolution and measurement processes can be expressed as [56]:

$$x_k = f(x_{k-1}, \theta_{k-1}, \omega_{k-1}) \tag{13}$$

$$y_k = h(x_k, \xi_k, \upsilon_k) \tag{14}$$

where x_k denotes the system state at time t_k, y_k is the observed degradation signal, $f(\cdot)$ and $h(\cdot)$ represent the state transition and measurement functions, respectively, θ_{k-1} and ξ_k are the model coefficients of the state transition and the measurement functions, respectively, and ω_{k-1} and υ_k denote process and measurement noise terms. The state transition is often modeled as a first-order Markov process, reflecting the assumption that the future system state depends only on its current condition.

In reliability applications, SSMs are commonly used to characterize the evolution of system health through continuous or discrete states, such as operational,

degraded, and failed conditions. Such a representation is well suited to prognostic health management (PHM) and predictive maintenance, where the estimation of remaining useful life (RUL) under non-stationary operating conditions is a key objective. By sequentially incorporating monitoring data, SSM-based models enable reliability assessment to move beyond fixed failure rates toward condition-dependent and adaptive predictions [55], [57].

A core advantage of SSMs lies in their capacity to handle uncertainty and partial observability, as they allow for the inference of latent variables or states from a series of emitted observed measurements [58]. To estimate these hidden degradation states and update reliability predictions as new data becomes available, Bayesian filtering techniques are frequently employed: Kalman filters are typically utilized for analytically tractable cases such as linear systems with Gaussian noise [59], whereas particle filters—a sequential Monte Carlo approach—are better suited for capturing the nonlinear characteristics of complex systems. These filtering methods have been successfully applied to power electronic modules, specifically IGBT devices, where internal degradation states cannot be measured directly, and observation data is often corrupted by interference noise [60].

Table 4. *Recent extensions of state-space models for reliability prediction*

Ref.	Application object(s)	Key contribution(s)	Limitations
[61]	Electrical circuit dynamical system	Proposed a dynamic model discrepancy quantification (DMDQ) approach to compensate for model bias arising from missing or inaccurate physical representations.	High computational cost; model bias may be indistinguishable from noise.
[55]	Rolling element bearings	Proposed a two-factor SSM to handle non-stationary operating conditions in the remaining useful life (RUL) prediction.	Predefined future profiles; limited operating variability; reliance on a single sensor.
[62]	Machine tool spindles	Integrated non-stationary operating conditions using a stochastic hybrid system for adaptive RUL prediction.	System complexity increases due to excessive operating states.
[60]	Insulated Gate Bipolar Transistor (IGBT) modules	Proposed particle filters-long short-term memory (PF-LSTM) to improve fault prediction for nonlinear and non-Markov systems.	Limited experimental data, reliance on curve fitting, and dependence on a single observed feature.
[63]	Robotic systems	Developed a hidden parameter recurrent state space model (HiP-RSSMs) to handle scenario-dependent dynamic behaviors.	Assumes fixed latent parameters; no reward integration for reinforcement learning.
[64]	Gearbox and bearing	Proposed a robust state-space modeling-reinforcement learning (SSM–RL) based RUL prediction model for unseen operating conditions.	Remaining identification errors assume stable RUL; depends on source data quality.
[58]	Non-stationary user models	Proposed likelihood-free inference (LFI) for SSMs with unknown dynamics to improve accuracy and simulation efficiency.	Misses long-term dependencies; struggles with non-Gaussian observation noise.

Classical SSM formulations nevertheless exhibit several limitations. They are often sensitive to model misspecification, and defining an accurate likelihood function can be difficult in practice. In addition, scalability becomes an issue when system dynamics or operating conditions vary significantly. Because of these drawbacks, recent work has increasingly focused on extending traditional SSMs. Typical efforts include incorporating additional sources of information, introducing learning capabilities, and developing more adaptive inference mechanisms. In particular, researchers have explored explicit modeling of time-varying operating conditions, the use of data-driven inference techniques, and the integration of SSMs with machine learning or reinforcement learning frameworks in order to improve robustness and adaptability.

Table 4 presents a selection of studies that introduce extensions of SSMs for reliability prediction and prognostics. The table indicates the physical systems under investigation and the particular limitations of conventional SSM formulations targeted in each study. In more recent studies, state-space models are no longer restricted to classical probabilistic formulations with fixed dynamics, and system behavior can be updated when additional information becomes available. By incorporating Bayesian inference procedures, data-driven learning techniques, and hybrid modeling strategies, these models support state estimation and prediction in the presence of uncertainty and changing operating conditions. As a result, state-space formulations continue to play an important role in reliability prediction for complex systems subject to dynamic environments.

3.2.2. Data-driven methods

Data-driven approaches draw upon theories of statistics and probability to examine historical and real-time data in an attempt to predict reliability. Rather than explicitly modeling physical failure processes, these approaches infer reliability as a latent system attribute learned from observed operational and condition-monitoring data. Consequently, reliability is treated as a conditional inference that depends on the data distribution, feature representation, and learning architecture employed, rather than as an intrinsic material or structural property. They can identify nonlinear relations and latent patterns in data without requiring in-depth knowledge of materials, structures, or failure modes, even under circumstances where explicit failure models are lacking [20]. This characteristic makes data-driven approaches particularly suitable for complex systems characterized by high-dimensional sensor information, strong variable interactions, and non-stationary operating conditions, where

traditional static reliability models become inadequate.

The major advantage of data-driven models has been the ability to use data collected during the functioning of the system as a way of updating the reliability of the system as more information becomes available. The data-driven reliability modeling approach has been based on the inferences of the data collected based on the operating realities that are captured. This approach has been relevant in the engineering of modern systems, as the operating conditions cannot be estimated in advance [65].

Despite their flexibility, the predictive accuracy of data-driven reliability models is inherently model-dependent. Different learning architectures, training strategies, and feature representations may yield varying reliability estimates when applied to the same dataset [66]. As a result, data-driven approaches do not provide a unique or absolute prediction of reliability, but rather a set of plausible inferences whose validity is confined to the domain spanned by the training data. It also illustrates the importance of model selection, validation techniques, as well as techniques for uncertainty estimation in the use of data-driven techniques in reliability assessment [67].

Current advances in machine learning, including deep learning, have led to more accurate predictions of reliability and degradation, with performance tending towards a saturating curve for well-instrumented data. It is, therefore, no longer the focus of current research, solely dependent on the accuracy of the prediction, but increasingly concerned with the reality of the computation being performed, such as the efficiency of computation, the latency of computation, the energy required for computation, and the embeddability of the computation [68]. Such considerations become even more important within the context of real-time health monitoring or reliability prediction within an industrial setting, where the resource requirements, including the uninterrupted nature of computation, become a factor that restricts the complexity of the computation [69].

From a methodological standpoint, it is important to distinguish between different categories of artificial intelligence techniques used in reliability analysis. Conventional machine learning methods are often favored when data availability is limited and interpretability is required [70], whereas deep learning approaches are more effective for extracting hierarchical features from large-scale, high-dimensional sensor data at the expense of increased computational demand [71]. Reinforcement learning, while less commonly applied to direct reliability estimation, has gained attention in maintenance planning and reliability-centered decision-making, where sequential optimization under uncertainty is required [72]. These distinctions indicate that no single AI paradigm is universally optimal and that the choice of method must be aligned with the specific reliability objective and operational context [20].

However, data-driven approaches have some inherent shortcomings, the most notable of which is the limited capability to distinctly separate the different ways in which a failure can occur. Various physical degradation mechanisms can result in the same set of observable data, hence undermining physical interpretability as well as potentially introducing a likelihood of mistakenly extrapolating the data based on a change in the operating environment or the preponderant physical degradation mechanisms [20], [73]. To address these limitations, hybrid approaches have been developed that combine physics-based and data-driven models to exploit the complementary strengths of the two paradigms. In such frameworks, physics-based models are used to provide causal structure and physically meaningful constraints. The role of data-driven components is to support adaptive updating and to improve predictive performance under real operating conditions [73–75].

Real-world applications of data-driven reliability methods include: (i) RUL prediction for IGBT modules in power converters, where LSTM-based models trained on collector-emitter voltage degradation signals have demonstrated accurate remaining-life estimates under variable mission profiles [60]; (ii) bearing fault detection and RUL prediction in industrial motors, where convolutional neural networks (CNNs) applied to vibration spectra have shown significant improvements over classical feature-engineering approaches; (iii) battery state-of-health estimation in EV applications, where data-driven models such as LSTM, GRU, and convolutional architectures are commonly trained and evaluated on public benchmark aging datasets such as NASA PCoE and CALCE; and (iv) prognostics for aerospace avionics, where transfer learning has been used to adapt failure prediction models from ground testing to in-flight operational data [6]. Within the same data-driven paradigm, recent studies published in this journal illustrate these capabilities for power-system assets: tree-based models such as gradient boosted decision trees have been used to estimate the insulation degree of polymerization and remaining useful life of power transformers from furanic-compound measurements [76], and fuzzy-logic schemes have been combined with conventional dissolved-gas-analysis ratio methods to improve transformer fault diagnosis [77]; machine-learning regression models have likewise been applied to estimate power output and detect performance degradation in solar photovoltaic systems under real operating conditions [78]. These applications collectively demonstrate that data-driven methods have matured from purely academic exercises to deployable industrial tools, provided that appropriate data governance, domain-specific model validation, and uncertainty management protocols are in place.

Beyond these practical examples, four expert-level concerns warrant explicit treatment, as they directly influence the deployment of data-driven reliability models in electronic systems.

(i) Uncertainty quantification. A critical challenge in deploying data-driven models for reliability prediction is the quantification of prediction uncertainty, which may arise from model parameter uncertainty (epistemic uncertainty) or from inherent data variability (aleatoric uncertainty). Several established uncertainty quantification (UQ) methods are applicable in this context, including Monte Carlo Dropout, deep ensembles, Bayesian neural networks, conformal prediction, and heteroscedastic neural networks. Recent benchmarking studies on remaining-

useful-life prognostics indicate that no single method universally outperforms the others and that the choice of UQ method should be guided by the specific reliability objective and deployment constraints. The specific references supporting these techniques are tabulated in the uncertainty-quantification entry of Table A.2 (Data-Driven Methods row) in Appendix A. These UQ approaches are especially important in electronic system reliability, where underestimating uncertainty can lead to premature maintenance or, more critically, unexpected system failure.

(ii) Robustness under domain shift. A fundamental limitation of data-driven reliability models is their sensitivity to distributional mismatch between training and deployment conditions, commonly referred to as domain shift or covariate shift. In reliability applications, domain shift arises when the operating conditions encountered during deployment (load profiles, ambient temperature, duty cycles) differ from those present in the training data. Domain adaptation techniques, including adversarial feature alignment, maximum mean discrepancy minimisation, and domain-invariant representation learning, aim to learn features that remain robust across source and target domains. Test-time adaptation further allows model parameters to be updated incrementally using unlabelled target data at inference time, without requiring labelled failure data from the new operational domain. Notably, embedding physics knowledge into the model structure can substantially improve domain robustness by anchoring predictions to physically plausible degradation trajectories even outside the training distribution, as developed in item (iv) below.

(iii) Data scarcity and label noise. Reliability data are inherently scarce: failures are rare events by design, labelled run-to-failure datasets are expensive to acquire, and censored observations are pervasive in field data. Label noise, that is, incorrect or imprecise failure labels, is also common when failure events are inferred from indirect sensor signals. Several approaches address these challenges. Few-shot and meta-learning frameworks enable model generalisation from limited labelled samples by learning transferable feature representations across systems or operating conditions. Semi-supervised learning exploits the typically abundant unlabelled condition-monitoring data together with sparse failure labels. Data augmentation strategies, including PoF-generated synthetic failure data, can expand the training distribution to improve coverage of rare failure scenarios. For label noise, robust loss functions and noise-aware training strategies have been shown to preserve model robustness in reliability-relevant classification settings.

(iv) Physics knowledge injection. The integration of physics knowledge into data-driven models can be achieved through three distinct architectures representing different depths of physics and data coupling. In grey-box models, a known physical structure (such as an Arrhenius-form degradation rate term or a Coffin-Manson damage accumulation law) is embedded within the model architecture, while data-driven components learn residuals or calibrate parameters that cannot be determined from physics alone; this preserves physical interpretability while gaining adaptability from data. In physics-informed neural networks (PINNs), governing equations (degradation kinetics, energy balance relationships, or failure mechanism laws) are incorporated directly into the training loss function as soft constraints, penalising predictions that violate known physical behaviour. In physics-guided parameter identification, data-driven inference methods (for example, Bayesian estimation or LSTM-based sequence models) are used to identify the parameters of an established physical model from operational data without requiring direct physical measurement; this approach has been demonstrated for electromagnetic relay reliability prediction in the recent literature.

New computing paradigms such as quantum computing and quantum-inspired computing have been explored for increasing the efficiency of learning and inference in reliability modeling [79–81]. For instance, variational quantum classifiers with domain-aware feature encoding have recently been applied to power transformer fault diagnosis, achieving high diagnostic accuracy with minimal quantum resources [82]. However, current literature is mostly exploratory in nature, and their applications are currently limited by the maturity level of the hardware and the formulation of the problem. Therefore, these should be viewed more as long-term research goals, rather than an immediate approach in place of data-driven, empirical, and physics-based reliability modeling.

3.2.3. Hybrid approaches

Hybrid approaches in reliability prediction can be defined as a framework that combines heterogeneous models of reliability in a single inference system. It is more about using physics models, empirical models, statistical models, or data models in a way that leverages their different strengths, rather than being a new approach to an individual model. As a promising new direction in modern reliability studies, a hybrid approach can be seen as a unifying paradigm connecting mechanism-level models and system-level models [21].

The rationale behind the development of combined reliability prediction approaches lies in understanding and overcoming the limitations of individual modeling methods when used alone. PoF reliability modeling has its strengths in understanding degradation and initiation of failures, but its implementation tends to be hampered by complexity and a large number of model parameters, thereby leading to scalability issues, especially when addressing large systems with less documentation. On the contrary, data-driven reliability modeling tends to have strengths in adaptability and efficient use of operational data, but its limitations exist in terms of physical interpretability and extrapolation, especially when faced with less representative data [83].

In terms of implementation, the process of hybridization can be achieved through different approaches to integration. In the case of sequential approaches to integration, the result or output of one paradigm model can be used as the input for the second paradigm model. This can include the use of PoF simulations to produce simulated data that relates to the failure or degradation that can then be used to produce data-driven models. This process can be beneficial for the

task of reliability analysis when actual data on failure events is difficult to acquire. By integrating data-driven models with the physically meaningful patterns inherent in the PoF simulations, the data-driven models can gain relevance beyond their original scope [84].

Parallel integration is another hybrid approach that has gained prominence, with physics-based and data-driven models being executed in parallel on the same system. In these models, the final reliability predictions are obtained through weighted fusion, ensemble averaging, and/or logic reconciliation of predictions for multiple models. The physics-based models basically act as physical consistency constraints that ensure data-driven models do not break the laws of degradation even when making predictions [85].

In reliability-oriented applications, physics-informed machine learning is commonly implemented by introducing physical relationships directly into the model training process. Physical constraints derived from governing equations, conservation relationships, or degradation kinetics are introduced directly into the training formulation, either through the optimization objective or through imposed structural conditions in the model. Predictions that deviate from known physical behavior are therefore limited during parameter estimation, preventing the model from following spurious patterns caused by noise or incomplete observations [86–88]. In practical reliability studies, this treatment is particularly relevant when failure-related data are scarce or when critical degradation regimes are not fully captured by the available measurements [89].

Three principal integration architectures for hybrid reliability models can be distinguished. In sequential integration, the output of a physics-based model (for example, PoF-simulated damage accumulation) serves as structured input or as a prior distribution for a subsequent data-driven model, enabling the latter to learn residual patterns beyond what the physics model captures. In parallel integration, physics-based and data-driven predictions are computed independently and fused through weighted combination or ensemble averaging, with the physics component acting as a consistency constraint that prevents physically implausible predictions. In embedded (physics-constrained) integration, physical laws are directly incorporated into the data-driven model architecture, through modified loss functions (as in PINNs), through physics-derived feature engineering, or through physics-consistent structural constraints, ensuring that the model respects known degradation kinetics throughout training and inference. Each architecture presents a different tradeoff between computational cost, flexibility, interpretability, and data requirements, and the choice should be guided by the lifecycle stage, the availability of a validated physical model, and the volume and quality of available operational data.

In addition to these integration strategies, hybrid reliability prediction frameworks often rely on specific combinations of established modeling techniques. A Bayesian physics-informed neural network enables probabilistic updating of battery health and aging states using new operational discharge data, while preserving physically grounded prior information [90]. State-space formulations, commonly implemented using Kalman filtering and its nonlinear extensions, are also widely used for RUL prediction, as they allow physics-based degradation models to be continuously corrected using observed data [91]. At the system level, digital twin implementations couple a virtual system model with real-time sensor measurements, allowing reliability predictions to be updated as operating conditions change [92–95].

Although hybrid reliability prediction methods offer clear benefits, their adoption in industrial practice remains limited by several practical constraints. Developing such models often requires expertise across materials behavior, failure mechanisms, statistical modeling, and algorithm implementation, which increases both development effort and coordination cost [85]. In addition, the lack of mature and standardized toolchains makes model integration, uncertainty handling, and result validation difficult, especially for large systems or safety-critical applications [84]. Hybrid approaches also place strong demands on data quality and on the fidelity of the underlying physical models; acceptable performance depends not only on the availability of operational data but also on how accurately the physical domain is represented. In many cases, these demands lead to substantial time and resource commitments that are difficult to justify for small organizations or for legacy systems with limited documentation [89], [90]. Addressing these issues will require more practical modeling workflows, improved tool support, and closer interaction between traditionally separate engineering disciplines.

4. Discussion

The purpose of this section is to offer a comprehensive overview of contemporary tendencies related to forecasting reliability in electronic systems, with a special focus on application specifics of different reliability prediction methodologies. In this section, instead of addressing modeling fundamentals and inherent strengths and weaknesses of each reliability prediction method, which were thoroughly described in Section 3, application aspects that emerge when these methodologies are used in practical engineering design problems are discussed. The overview of application aspects of different reliability prediction approaches is divided into six main categories: empirical based, physics-of-failure, life testing, state space model, data-driven, and hybrid/fusion methodologies.

4.1. Current challenges

While Section 3 examines individual reliability prediction approaches from a methodological perspective, the present subsection synthesizes these methods from an application and lifecycle standpoint. In practical engineering workflows, reliability prediction evolves as the product progresses from early conceptual design through detailed development, verification, and operational deployment. As a result, the effectiveness of a given method depends on the information available at each stage of the lifecycle, as well as on the associated modeling objectives and implementation constraints.

Tables A.1 and A.2 in Appendix A summarize the six previously discussed reliability prediction approaches

across eight feature dimensions, offering a comprehensive comparative view to aid in evaluating their practical applicability across different contexts and lifecycle stages. Table A.1 addresses required inputs, key assumptions, primary outputs, and calibration needs, while Table A.2 addresses uncertainty handling, interpretability, lifecycle stage applicability, and typical failure modes.

4.1.1. Lifecycle-dependent suitability and information mismatch

An essential issue emerging from Tables A.1 and A.2 is that there is no universally applicable method for predicting reliabilities at different stages of the product life cycle. At early stages, only empirical models can be employed because of a lack of design detail and the absence of system-specific information. At a later stage of development, PoF modeling increasingly utilizes detailed product information, especially materials, geometry, and loading [11]. At the operational level, it would be difficult to maintain models requiring detailed information [12], [88].

In the operational phase, data-driven and state-space methods become more important as monitoring data becomes known. However, these methods remain highly ineffective during earlier lifecycle phases, resulting in disjointed reliability assessment processes themselves [69], [84]. Such lifecycle-dependent discrepancies between method needs and data availability make it more difficult to maintain homogeneity with regard to predictions about system reliability.

4.1.2. Discontinuity of reliability modeling across lifecycle stages

Another challenge is the limited continuity of reliability prediction methods across different stages of the product lifecycle. In many practical cases, reliability analyses are carried out separately at each stage, and models, parameters, or insights are only marginally transferred from one phase to the next. For example, empirical estimates developed during conceptual design are seldom incorporated into subsequent PoF analyses [11], while PoF-based insights are rarely used to inform the formulation of data-driven or state-space models during operation [84].

Consequently, reliability prediction tends to take the form of a set of loosely connected assessments rather than a modeling framework that is refined progressively over time. Such fragmentation results in the loss of accumulated knowledge and ultimately diminishes the contribution of reliability analysis to long-term decision making [2], [14].

4.1.3. Practical deployment constraints beyond methodological considerations

Beyond methodological suitability, the real-world deployment of reliability prediction approaches is often limited by practical factors, including the availability of sensing infrastructure, data quality, computational capacity, and organizational preparedness [14], [68]. Although state-space and data-driven models are theoretically robust, their effective use depends on continuous and reliable condition monitoring, together with well-established procedures for data processing and ongoing model maintenance [62]. In many industrial settings, however, these prerequisites are only partially met [65], [69].

As a result, the performance of a reliability prediction method is frequently governed less by its theoretical strengths than by how feasibly it can be implemented within a specific operational context [1], [14]. The resulting disparity between methodological potential and practical applicability has therefore remained a recurring issue in reliability engineering practice [6], [21], [89].

4.1.4. Hybrid approaches as an emerging but immature solution

Hybrid-fusion methods, which seek to integrate physics-based understanding with data-driven learning, are frequently cited as a promising avenue for addressing the limitations of single-paradigm approaches [20]. As indicated in Tables A.1 and A.2, hybrid methods have the potential to support reliability prediction across multiple lifecycle stages by combining mechanistic interpretability with adaptability to operational data [90].

Despite this potential, the adoption of hybrid approaches in industrial practice is still relatively limited. Their practical implementation typically involves substantial computational effort, strong system dependence, and a considerable degree of expert involvement. In addition, standardized workflows and well-defined validation protocols for hybrid reliability prediction have not yet been fully developed. As a result, hybrid methods are still mainly explored in research settings and have not yet reached the level of maturity required for broad industrial deployment [85].

4.1.5. Computational considerations for hybrid approach deployment

Beyond methodological maturity, large-scale industrial deployment of hybrid reliability prediction faces three principal computational challenges, each of which admits a corresponding mitigation strategy.

(a) Model complexity and inference cost. Physics-based components such as FEM-based thermal or mechanical simulations are computationally intensive, and their coupling with iterative data-driven inference (for example, Bayesian updating, particle filtering) can render real-time deployment infeasible for large system assemblies. Mitigation strategies include surrogate or reduced-order models (ROMs) that approximate the physics model at a fraction of the computational cost, and model compression techniques (pruning, quantisation, knowledge distillation) that reduce the inference footprint of the data-driven component.

(b) Data and model synchronisation overhead. Digital twin implementations require continuous synchronisation between the physical asset and its virtual replica, generating substantial communication and computational overhead at scale. Edge computing architectures, in which lightweight inference models are deployed at the sensor or controller level with aggregation and model updates performed in the cloud, are a recognised mitigation strategy for distributed large-scale installations [68], [69].

(c) Expert resource requirements. Developing and maintaining hybrid models requires cross-domain expertise (materials science, failure physics, statistical modelling, software engineering), which constitutes a

practical scalability constraint for organisations without dedicated reliability modelling teams. The emergence of physics-informed machine learning frameworks and digital twin platforms (such as ANSYS Twin Builder, Siemens Xcelerator), which provide structured interfaces between simulation and data analytics, is progressively reducing the specialist effort required for hybrid model implementation.

4.2. Future research directions

As mentioned in Section 4.1, state-of-the-art reliability prediction models work well in given domains but still suffer from some overt shortcomings. The concerns about scalability, dependency on the availability of data, restricted generalized capability, and lack of interpretability still lie unresolved. These problems are generally likely to aggravate with the increased complexity of electronic systems and their exposure to dynamically varying and uncertain environments. Therefore, the focus of research in the upcoming years must lie in improving the robustness of models and dealing with uncertainty in a proper manner. In addition, future investigations should aim to bridge the gap between analytical modeling and real-world deployment, ensuring that reliability prediction becomes actionable within design, validation, and maintenance workflows [96].

4.2.1. Physics-informed learning

One promising area of research is related to the development of physics-informed learning models where physics-related constraints and failure mechanisms are explicitly incorporated into data-informed models. By incorporating governing equations into the learning process (e.g., through neural network loss functions), these models can integrate noisy observations with mathematical formulations and remain effective for ill-posed inverse problems [97]. Such models are able to leverage physics-related understanding of failure mechanisms to make them less reliant on data during the learning process. Physics of failure is appropriately suited to be used in the early stages of operation, where data is limited but physics-related understanding is available [21].

To move this direction forward, future studies could explore how to encode specific degradation mechanisms (e.g., electromigration, solder fatigue, or dielectric breakdown) into flexible learning architectures without sacrificing scalability. Another challenge lies in quantifying how physical constraints influence model outputs when field data progressively accumulates. Addressing these issues would open opportunities for physics-informed learning to be used not only for early-life assessment but also for long-term system monitoring.

4.2.2. Transfer learning and domain adaptation

Transfer learning methods and domain adaptation are effective at devising solutions to the issues caused by data scarcity and domain discontinuity [98]. In contrast to building separate reliability models based on each system or environment, these methods support the transfer of knowledge gained from previous systems or from accelerated tests or high-fidelity simulations. Future work should be focused on domain transfer methods that preserve physical consistency with system designs that differ.

Further efforts are also required to determine how to schedule knowledge transfer across different lifecycle phases and varying stress conditions, where naive transfer may introduce bias or degrade performance. Practical scenarios such as transferring models from prototype to mass production, or from bench testing to field operation, remain underexplored and represent important research opportunities. Successful developments in this direction would contribute to reducing the cost of data collection and accelerating the deployment of predictive models.

4.2.3. Digital twins and cyber–physical reliability frameworks

Digital twin technology provides a common ground for the integration of physics models and data-driven model updates and uncertainty quantification. Using digital twins that evolve side by side with the asset allows predictions related to the reliable performance of such assets to be improved gradually using feedback and data obtained through measurement and simulation [99]. Further development is required in model synchronization and computational efficiency [100].

There is also a need to establish standardized interfaces that allow different simulation tools, embedded measurements, and reliability models to operate coherently across the hardware–software boundary [101]. Another promising direction involves extending digital twins to account for degradation behavior during the full lifecycle, rather than focusing only on operational performance. These expansions would support cyber–physical reliability frameworks where models do not merely reflect the system but also influence control and maintenance decisions in real time [102].

To accelerate the practical deployment of digital twin–based reliability frameworks, two complementary standardisation paths warrant attention. First, standardised data exchange formats and application programming interfaces between simulation tools (FEM solvers, PoF models), condition-monitoring platforms, and machine learning frameworks would substantially reduce the integration effort currently required for hybrid model development. Emerging standards such as the Functional Mock-up Interface (FMI/FMU) for co-simulation and the ONNX format for ML model exchange represent initial steps in this direction. Second, commercial digital twin platforms (such as ANSYS Twin Builder, Siemens Xcelerator, and similar industrial offerings) are progressively providing structured environments that integrate physics simulation, real-time data ingestion, and analytical model deployment within a single toolchain, thereby reducing the interoperability challenge for organisations that adopt these platforms for asset management.

4.2.4. IoIT-enabled monitoring and edge intelligence

The increased usage of the Internet of Intelligent Things (IoIT) promotes distributed sensing and online reliability prediction calculation [68]. The focus of future research should lie in designing models of reliability that behave well even with limited calculation capabilities and resilience to uncertainties of data and communication delays. The issues of data governance and cybersecurity would also play critical roles in reliable deployment.

In addition, algorithmic strategies capable of performing lightweight incremental updates at the edge will likely become necessary, given that centralized processing is not always feasible in large-scale installations. Real-world application domains include health monitoring in real-time smart manufacturing cells, condition monitoring in embedded power electronics, and autonomic systems in environments with low communication connectivity. These domains serve as the driving force for research in model reduction, communication-efficient inference, and adversarial data processing.

4.2.5. Uncertainty modeling and emerging computational paradigms

One of the major challenges around reliability prediction remains uncertainty. It becomes difficult to interpret and apply the results of models in the presence of uncertainty associated with failure mechanisms, as well as the uncertainty in the operating conditions [103]. Therefore, the future of research in the field of reliability prediction might revolve around the study of ways to interpret uncertainty in a reliability prediction problem. At the same time, developments in computational paradigms, such as the newly emerging quantum paradigm, might provide long-term solutions to the increasing computational requirements of reliability predictions [80].

Future studies could investigate how to represent different forms of uncertainties in more transparent ways that are amenable to use by engineers during design review, qualification, and maintenance activities. On a more speculative level, research on accelerated platforms, such as neuromorphic computing architectures, in combination with quantum computing platforms, might be useful in easing potentially large-scale model simulation and sensitivity analysis tasks. While practical implementations remain limited, these directions highlight long-term opportunities for handling complex system models that exceed the capabilities of conventional computing.

4.2.6. Integration with PHM and decision support

Next steps for future studies include further integrating reliability predictions into Prognostics and Health Management (PHM) concepts. It is necessary to relate reliability models to tasks such as maintenance planning and risk management directly and to relate these to overall decision-making processes over the entire lifecycle through accurate predictions and interpretable results [104].

Additionally, stronger coupling between reliability metrics, health indicators, logistics constraints, and operational objectives could create more realistic decision-support environments. For instance, integrating remaining useful life estimates with spare-part strategies or production scheduling could help organizations manage cost and downtime simultaneously [105]. Such integration would help position reliability models not merely as analytical tools, but as active contributors to asset management, design validation, and continuous improvement processes.

The practical adoption of hybrid reliability prediction within PHM-driven decision support is further constrained by the relative scarcity of standardised toolchains and reference implementations. Two complementary directions can address this constraint. First, community-driven repositories of validated hybrid reliability model implementations for common electronic component types (IGBT modules, electrolytic capacitors, solder joints) would accelerate adoption by allowing practitioners to adapt established architectures rather than building from scratch. Second, future revisions of reliability engineering standards (such as IEC 62380, FIDES, and MIL-HDBK-217F successors) could explicitly incorporate data-driven and hybrid method provisions, providing a normative framework that guides model development, validation, and documentation requirements within industrial quality management systems. Together, these two directions would help embed hybrid reliability prediction within the broader PHM and decision-support ecosystem.

5. Conclusion and perspectives

This study examines a broad set of reliability prediction approaches applied to electronic systems, covering empirical techniques, physics-of-failure–based models, and methods driven by operational data. The discussion shows that these approaches are rarely interchangeable in practice, as their usefulness depends strongly on the information available, the modeling intent, and the stage of the product lifecycle at which they are applied. While individual methods have shown good performance under particular conditions, challenges associated with scalability, dependence on data availability, transferability across operating environments, and practical interpretability continue to be observed.

One observation arising from this study is that reliability prediction cannot be addressed satisfactorily through a single modeling framework applied uniformly over the system lifecycle. More realistic solutions are expected to emerge from approaches that link physical descriptions of failure behavior with learning-based components, enabling models to function under limited data while still adjusting to changes encountered during operation. In this sense, hybrid strategies provide a practical route toward reliability assessments that support engineering decisions rather than remaining purely analytical exercises.

The future will demand an increasingly integrated approach to modeling, monitoring, and decision support in the prediction of the reliability of electronic systems. A focus on continuity of predictions in the context of uncertainty and tractability of computation under industrial constraints will steer the prediction of reliability from the current focus on analysis to the inclusion of prediction in the context of system design, maintenance, and operation.

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APPENDIX A. COMPREHENSIVE FEATURE MATRIX OF RELIABILITY PREDICTION METHODS

This appendix consolidates the comprehensive feature matrix that supports the comparative analysis presented in Section 4.1. The matrix evaluates the six reliability prediction methods reviewed in this paper against eight feature dimensions identified as relevant for method selection in practical engineering workflows. To preserve readability within the journal layout, the matrix is split into two complementary tables: Table A.1 covers the input-related and output-related dimensions (required inputs, key assumptions, primary outputs, and calibration needs), while Table A.2 covers the application-related dimensions (uncertainty handling, interpretability, lifecycle stage applicability, and typical failure modes). Both tables share the same six-method schema, allowing direct cross-method comparison along each dimension.

While Table A.1 specifies how each method is parameterised and what it produces, Table A.2 characterises how each method behaves in deployment, with particular attention to uncertainty handling, transparency to engineers, and applicability across lifecycle stages.

Several cross-method observations emerge from Tables A.1 and A.2. First, no single method dominates across all eight dimensions: empirical and PoF approaches offer high interpretability but limited adaptability, whereas data-driven methods offer superior adaptability at the cost of physical transparency. Second, calibration needs scale steeply with method complexity, from minimal (empirical, drawing on standardised databases) to extensive (hybrid, requiring dual calibration of physics and data components). Third, uncertainty handling is the dimension with the greatest qualitative variation across methods: deterministic for empirical, statistical for life testing, probabilistic and state-based for SSMs, and model-dependent (with multiple competing UQ techniques) for data-driven. Fourth, the lifecycle stage applicability dimension confirms the lifecycle-oriented mapping introduced in Section 1: each method category occupies a distinct portion of the product lifecycle, with hybrid approaches uniquely capable of spanning late design through in-service operation. These observations support the position taken in Section 4.1 that method selection should be governed primarily by the lifecycle stage and the available information, rather than by perceived methodological sophistication alone.

Table A.1. *Comprehensive comparative feature matrix of reliability prediction methods, Part I: Inputs, assumptions, outputs, and calibration [2], [18], [19], [21], [22], [25]*

Method	Required inputs	Key assumptions	Primary outputs	Calibration needs
Empirical Based	Component type, operating temperature, voltage stress, quality class, environment category	Constant failure rate (exponential distribution); stationary operating conditions; correction factors representative of field behavior	Predicted failure rate λ, MTTF, MTBF	Minimal: parameters from standardized databases (MIL-HDBK-217F, Telcordia SR-332)
PoF	Material properties (activation energy, Young's modulus, coefficient of thermal expansion), geometry, mission/stress profile (thermal cycles, voltage, vibration)	Dominant failure mechanism is identifiable; stress–damage relation follows known physical law (Arrhenius, Coffin-Manson, Eyring)	Time-to-failure (TTF), damage accumulation index, RUL estimate	Material constants from characterization tests or literature; FEM simulations often required
Life Testing	Failure time data from test specimens under controlled stress levels	Life–stress relationship is valid (Arrhenius, inverse power law); no new failure mechanisms activated under accelerated stress	Reliability function $R(t)$, MTTF, Weibull parameters (β,η), B-life	Statistical fitting (maximum likelihood estimation, Bayesian) to test data; stress-acceleration model validation required
SSMs	Sequential condition-monitoring data (sensor signals, degradation indicators), initial state distribution	Markov property (future state depends only on current state); state transition and measurement models are specified	Filtered/predicted hidden degradation state, RUL distribution, failure probability	State transition and noise parameters via expectation-maximization algorithm or Bayesian parameter estimation
Data-Driven	Labeled operational data (sensor readings, health indicators, failure labels)	Training distribution is representative of deployment conditions; sufficient labeled failure data are available	Predicted RUL, failure probability, health index, anomaly score	Hyperparameter tuning (cross-validation, Bayesian optimization); model retraining under distribution shift
Hybrid	Combination of physical model parameters and operational monitoring data	Physics model captures dominant degradation structure; data-driven component corrects residuals or calibrates unknown parameters	Physics-consistent RUL, failure probability with uncertainty bounds	Physics model calibration plus data-driven model training; interface definition between components

Table A.2. *Comprehensive comparative feature matrix of reliability prediction methods, Part II: Uncertainty handling, interpretability, lifecycle stage, and typical failure modes [2, 18, 19, 21, 22, 25, 106, 107, 108, 109]*

Method	Uncertainty handling	Interpretability	Lifecycle stage	Typical failure modes
Empirical Based	Deterministic; no formal uncertainty quantification (UQ); variability absorbed into correction factors	High: transparent formula, industry-recognized structure	Conceptual design, early feasibility assessment	Generic electronic component failure (no mechanism specificity)
PoF	Limited in classical PoF; recent hybrid PoF–Bayesian frameworks incorporate probabilistic inference	High: mechanistic, physics-grounded	Detailed design, material selection	Electromigration, solder fatigue, dielectric breakdown, bond wire liftoff, corrosion
Life Testing	Statistical confidence intervals; censored data analysis via maximum likelihood estimation or Bayesian methods	Moderate: statistical distributions with less physical insight	Verification and qualification testing	Wear-out, fatigue, thermally-activated failures
SSMs	Explicit probabilistic state estimation (Kalman filter for linear/Gaussian; particle filter for nonlinear systems)	Moderate: latent state variables may lack direct physical meaning	In-service monitoring, predictive maintenance	Gradual degradation (wear, fatigue, aging) detectable through precursor signals
Data-Driven	Model-dependent: Monte Carlo Dropout [106], Deep Ensembles [107], Bayesian neural networks, conformal prediction [109]; comprehensive benchmark in Basora et al. [108].	Varies: low (deep learning, black-box); moderate (gradient boosting, attention-based); high (linear, tree-based models)	Operational phase with continuous condition monitoring	Data-dependent; no explicit physical mechanism discrimination
Hybrid	Inherited from both paradigms; physics constraints prevent physically inconsistent uncertainty bounds	Moderate-to-high when physics component is dominant; lower when deep neural networks are used	Late design validation through in-service operation	Multi-mechanism, system-level failures that single-paradigm methods cannot capture alone